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Outstanding Student & PhD candidate Presentation contest

Integrating Numerical Methods to Assess Failure Probability of Rock Slopes Considering Uncertainties in Mechanical and Hydraulic Properties

Akash Chakraborty [a,*], Kuang-Tsung Chang [a]

[a] Department of Soil and Water Conservation, National Chung Hsing University, Taichung 402, Taiwan

* Corresponding author. Email: akash100c@gmail.com

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1. Background motivation

Typhoons and extreme rainfall conditions typically lead to failure and collapse in rock slopes with steep geological features. The Lushan slope, located in the central region of Taiwan, has been undergoing sliding due to similar rainfall conditions over the past decades. In regular slope stability analyses, the average values of strength parameters are used to estimate the factor of safety (FS). However, natural slope materials often exhibit significant variability, making it challenging to assess slope stability based solely on fixed parameter values. Due to this inherent uncertainty in geotechnical properties, evaluating the probability of slope failure has become essential for a more realistic and reliable assessment of slope stability. In this study, the uncertainty of mechanical and hydraulic parameters is considered to explore the probability of failure in rock slopes, which can be used as a reference for the risk assessment and early warning systems of large-scale collapse. Stochastic Finite Element Method (SFEM) analysis was conducted through Monte Carlo Simulation (MCS) method to perform random sampling and generate combinations of parameters as random variables with uncertainty.

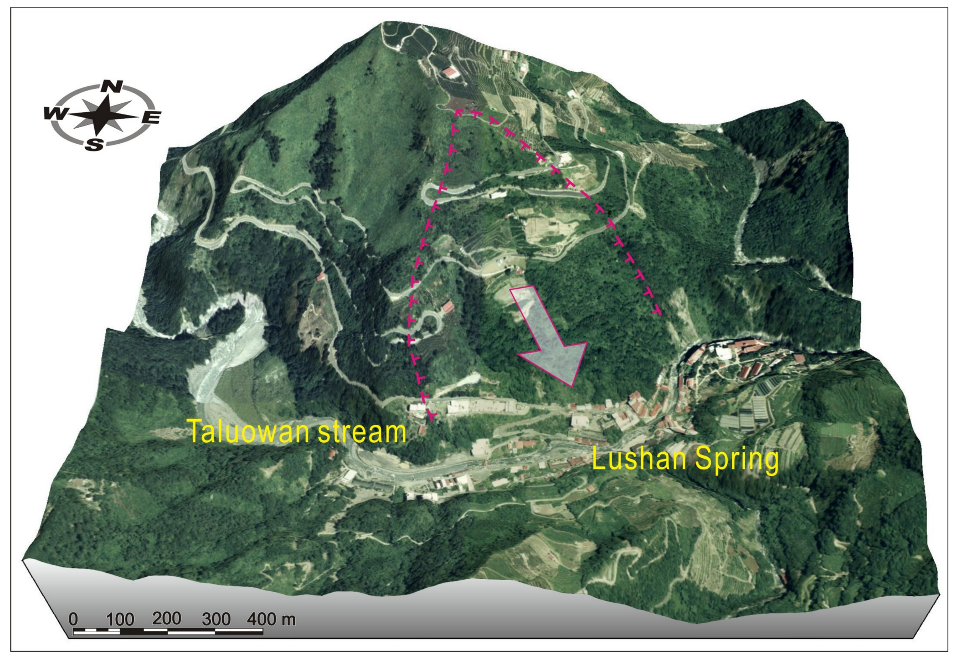


Figure 1: Panoramic view of the landslide area in Lushan

2. Slope model

- The slope geometry was extracted from a 5m DEM model using ArcMap.
- The sliding surface in this study is based on the Central Geological Survey's investigation of the Lushan slope sliding surface through inclinometers. The maximum sliding depth is about 90 to 100 meters. The toe is located near the Taluowan River valley.
- The Mohr-Coulomb (MC) model and the Van Genuchten (VG) model were used to represent the mechanical and unsaturated hydraulic behavior of the slope, respectively.
- The VG parameters g_a (air entry value), g_n, and g_l (fitting parameters) are used to match the groundwater level (GWL) and hydraulic conditions of the real slope.
- The GWL data of Typhoon Morakot, Typhoon Saola, and Typhoon Soulik were collected from A21, A24, and A25 borehole data from the Central Geological Survey.
- The rainfall events are introduced in the model through the infiltration boundary on the surface of the slope.

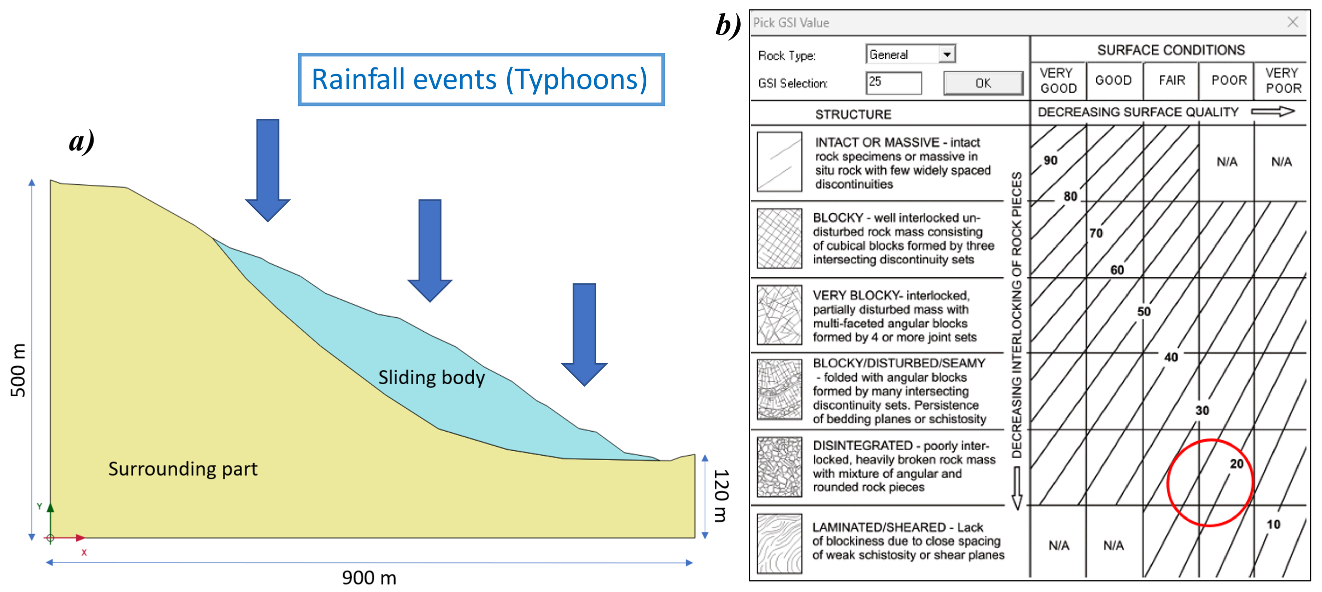


Figure 2: a) Model geometry b) GSI range of Lushan sliding area

Table 1: Model geological parameters (Chang, 2015)

	Slate Sliding body (Mohr-Coulomb)	Sandy slate Surrounding part (Linear Elastic)
Unit weight (kN/m³)	26.2	26.2
Saturated unit weight (kN/m³)	26.4	26.4
Young's modulus (kN/m²)	1E7	1.5E7
Poisson's ratio	0.3	0.3
Cohesion (kPa)	84	
Friction angle (˚)	28.9	
Permeability (m/h)	0.01	0.01

3. Methodology

- The simulation consisted of a gravity loading initial stage, followed by a no rainfall transient stage of 500 hours to stabilize the GWL before the rainfall event, and the final rainfall event stage.
- The unsaturated parameters g_a and g_n were back-calculated through transient analyses to simulate the rise of GWLs according to the real monitored data for model verification (g_l was fixed at 0).
- The back calculation was done by matching the GWL rise of two rainfall events – Typhoon Saola and Soulik, and the Root mean square error (RMSE) method (Yang et al. 2019) was used to get the best fit and minimum errors.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(M_i - S_i)^2}$$

- Three uncertainty parameters were selected for the Monte Carlo sampling analyses – ϕ, g_a, and g_n. The ModelRisk software was utilized to generate random values for 100 sets.
- The three sigma rule (Duncan, 2000) was used to calculate the standard deviation of the 3 parameters using their Highest Conceivable value (HCV) and Lowest Conceivable value (LCV) obtained through back calculations from GWL data.

$$\sigma = \frac{HCV - LCV}{6}$$

- The friction angle range was determined and calculated from the GSI values used in Chang, 2015, using Roclab software.
- Finally, the factor of safety (FOS) calculations were conducted through the strength reduction method in Plaxis 2D for 100 simulations and the probability of failure was calculated.

$$P_f = Pr[FOS < 1]$$

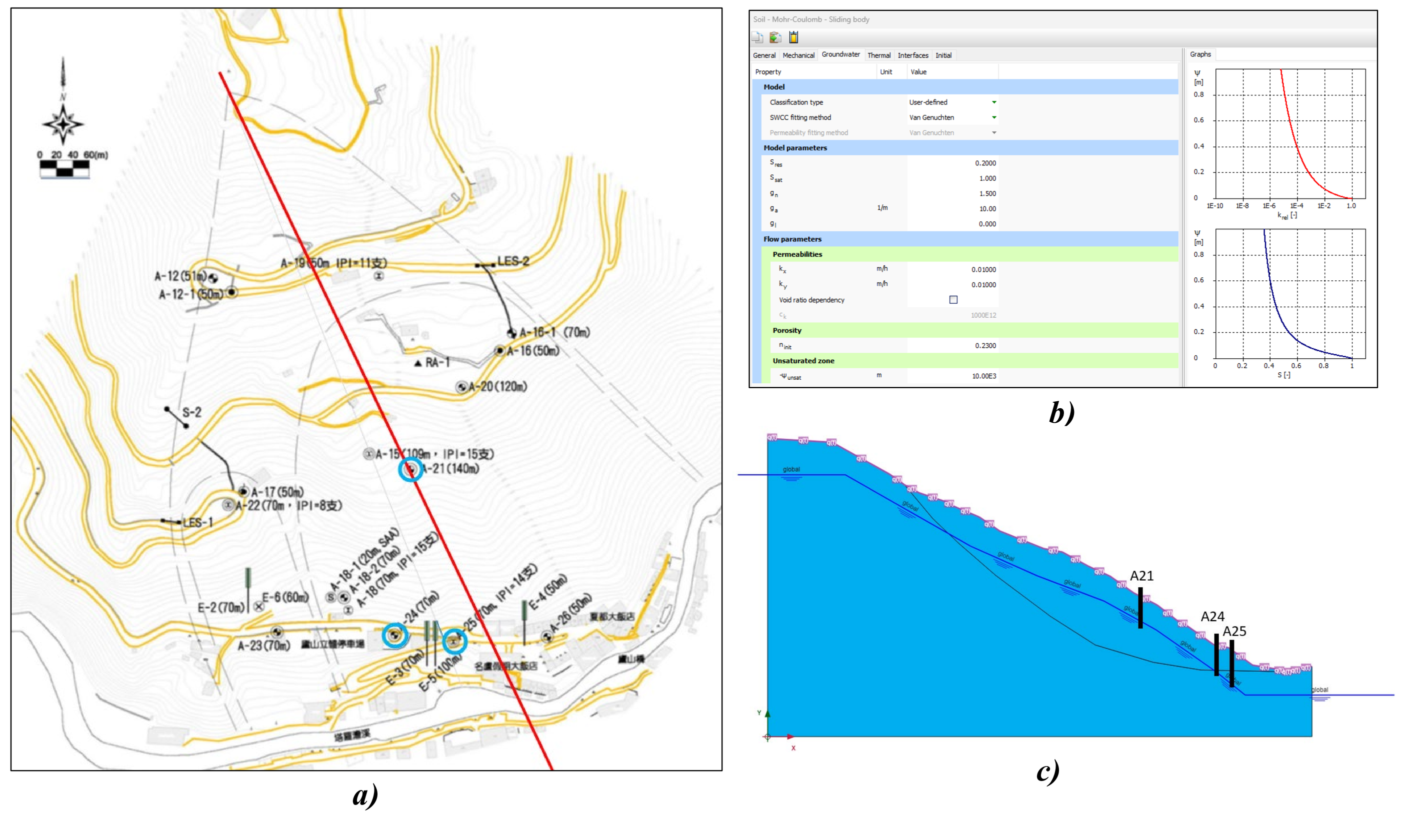


Figure 3: a) Boreholes for GWL monitoring b) SWCC curves c) Flow conditions in model

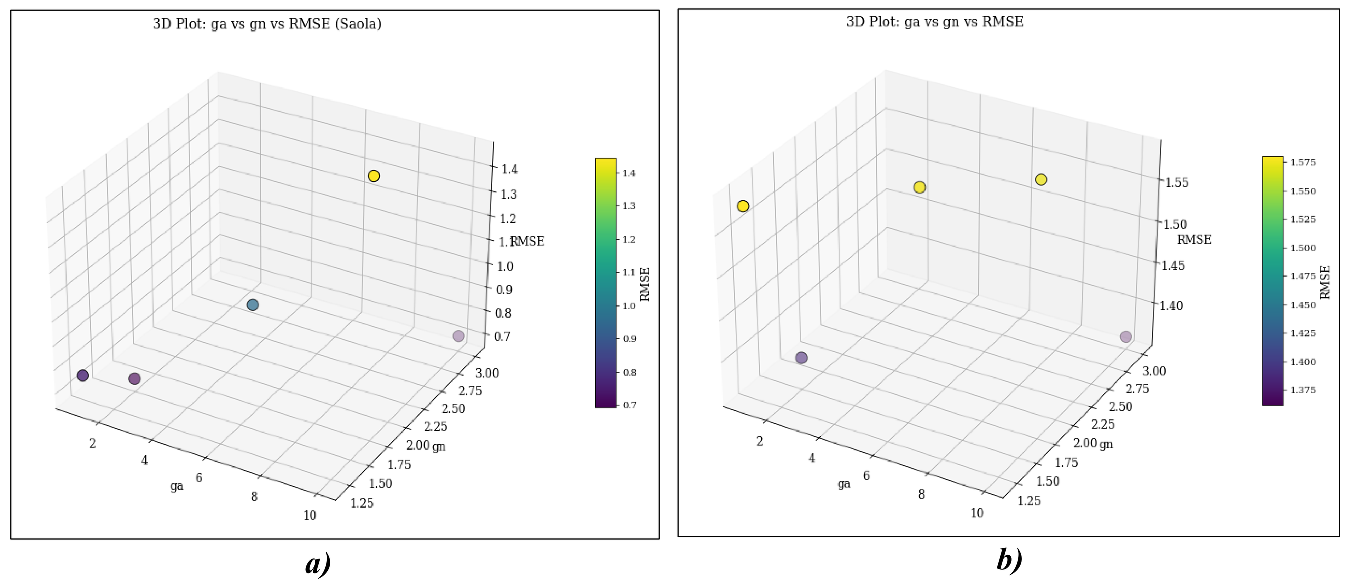


Figure 4: Correlation of RSME with g_a and g_n for matching GWL rise a) Saola b) Soulik

4. Results

- The change in groundwater level before and after the rainfall events was observed in the output results.
- The probability distributions of the three uncertainty parameters were chosen to follow the normal distribution.
- The Monte Carlo sampling method from ModelRisk determines different parameter combinations for FOS calculations.
- 39 out of 100 simulations had FOS ≤ 1. Average FOS was found out to be 1.026.

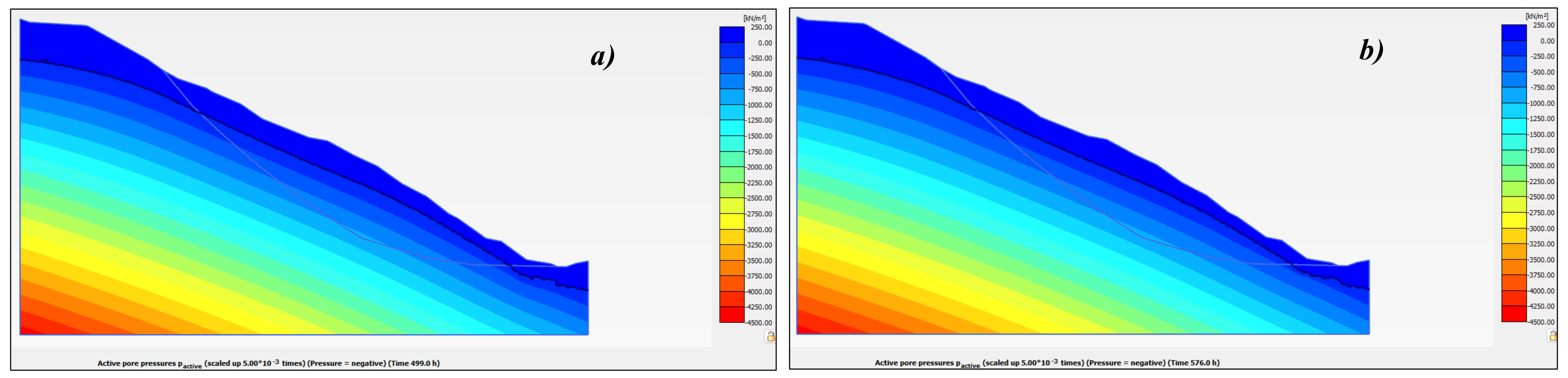


Figure 5: Rise of groundwater level after the Morakot event in transient analysis a) Before rainfall b) After rainfall

Table 2: Three sigma rule variables

Parameters	ϕ (˚)	g_a(1/m)	g_n
Highest Conceivable value (HCV)	31	10	3
Lowest Conceivable value (LCV)	24	1	1.1
Average/Mean (μ)	27.5	5.5	2.05
Standard deviation (σ)	1.667	1.5	0.316

Table 3: 100 sets from MCS

Sl. No.	ϕ	ga	gn	FOS
1	28.2691	4.153694	1.859286	1.01
2	29.24245	6.421069	1.999386	1.039
3	28.86129	5.399702	1.774992	1.027
4	27.57148	5.092852	1.964074	1.002
5	28.01115	6.851502	2.115822	0.988
6	27.9657	5.534274	1.763569	1.002
7	29.11176	5.880638	1.926961	1.037
8	26.7884	5.266198	2.178366	0.979
9	28.39493	4.482908	2.212032	0.998
10	28.52236	4.724582	1.585155	1.015
11	27.41151	5.220277	1.535597	1
12	27.63646	4.724828	1.762443	1.047
13	26.38886	6.489844	1.644782	0.952
14	28.27093	5.96412	1.956975	1.006
15	27.63398	5.663602	2.038146	0.97
16	26.47359	4.116358	2.111989	0.96
⋮	⋮	⋮	⋮	⋮
96	28.09371	4.550164	2.33393	1.003
97	26.9604	4.579418	2.554732	0.981
98	28.17564	5.186724	1.754643	1.117
99	26.15207	5.171772	1.985465	1.095
100	26.12903	5.324163	1.831242	1.088

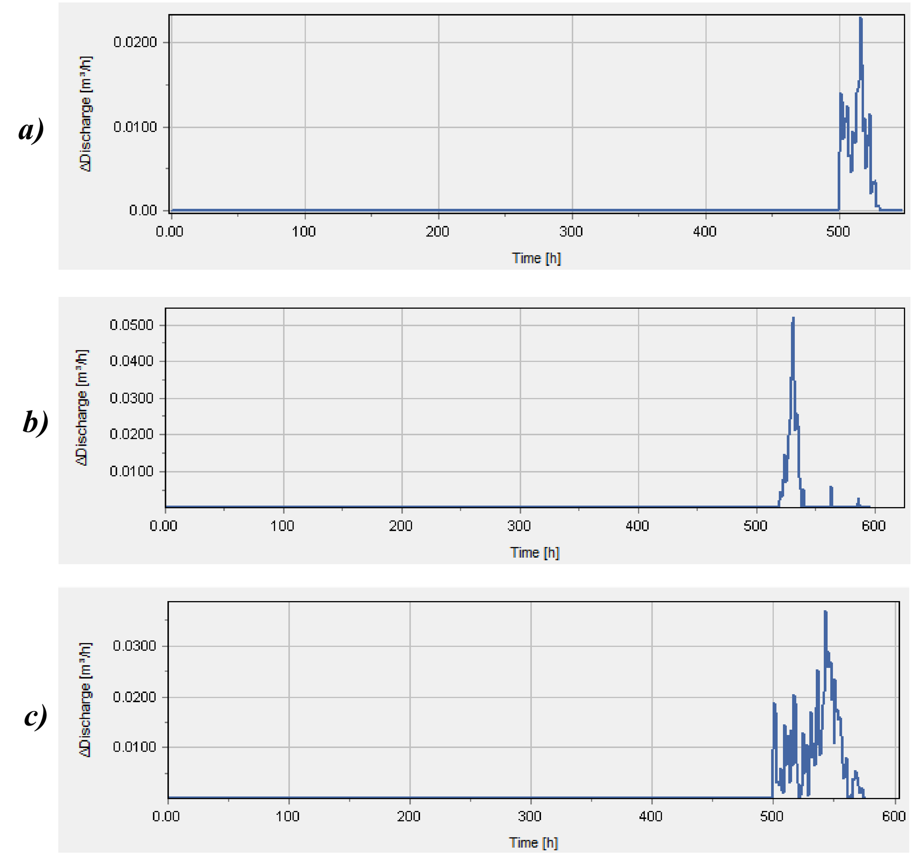
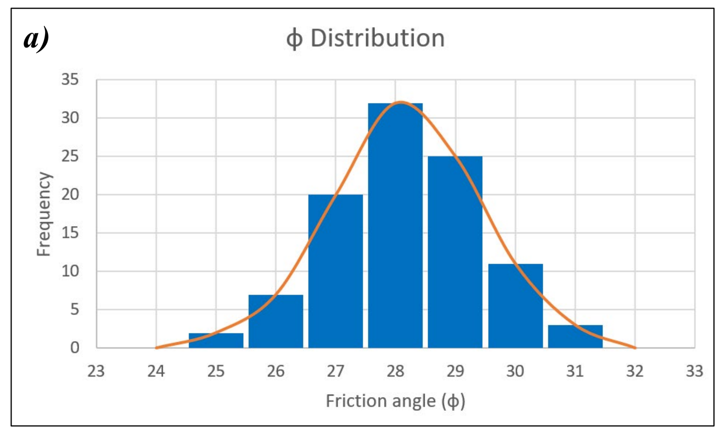
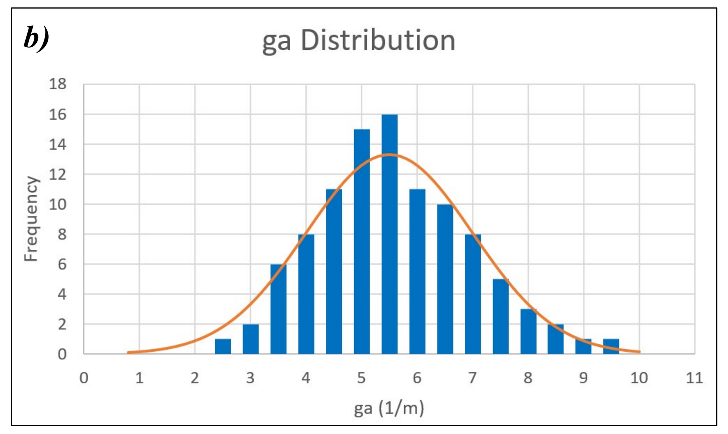


Figure 6: Infiltration plot (500 hours no rain + Rainfall event) a) Saola b) Soulik c) Morakot





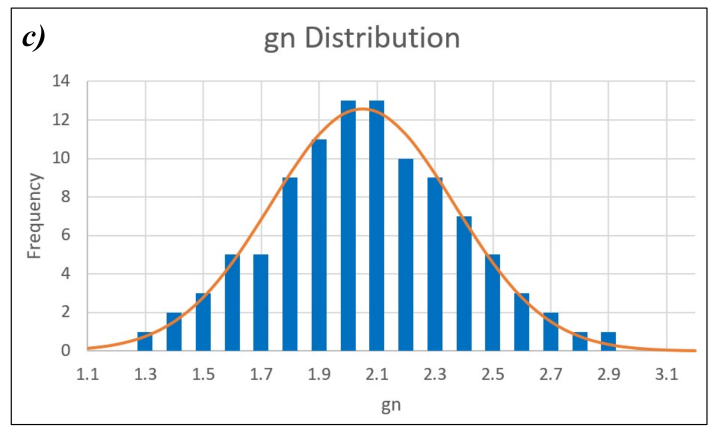


Figure 7: Mechanical and hydraulic parameter distributions

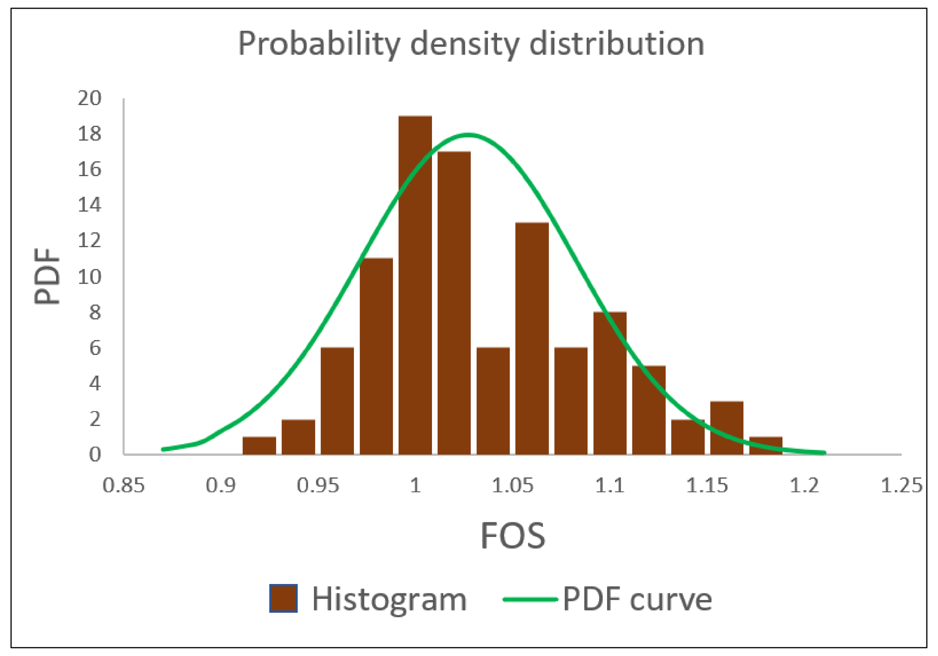


Figure 8: Probability density distribution of FOS of Lushan slope

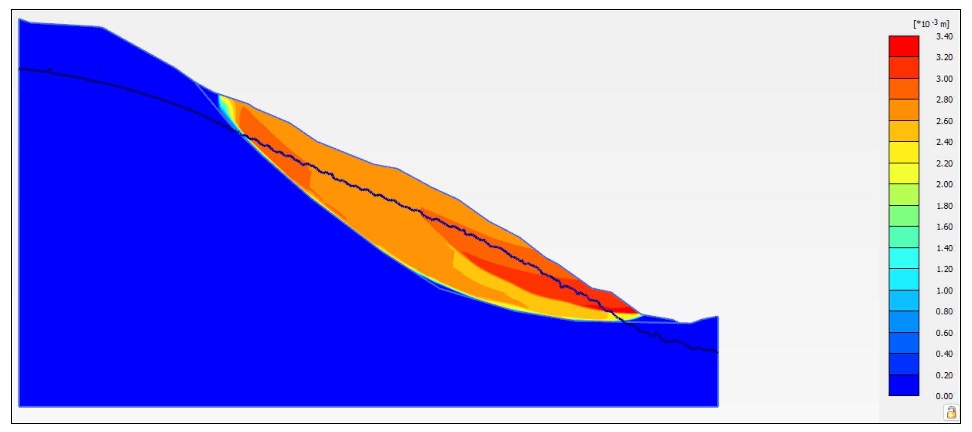


Figure 9: Incremental displacement plot at ϕ = 28.9˚, g_a = 2 and g_n = 1.5

5. Conclusions

- This study uses FEM software for slope stability analyses and considers uncertainty in friction angle and unsaturated VG parameters to provide a reliable probability analysis as a reference.
- The GWL changes observed in the simulations were consistent with the borehole monitored data, therefore, this model is effective for subsequent use.
- The probability of failure of the Lushan slope under the Typhoon Morakot event is 39 %.
- Future work focuses on improving the model into 3D, running more simulations over 100, and the use of variable rainfall patterns.

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7. Author Details

Akash Chakraborty: Ph.D. candidate, Dept. of Soil and Water Conservation, National Chung Hsing University, Taichung, Taiwan (akash100c@gmail.com).

Kuang-Tsung Chang: Professor, Dept. of Soil and Water Conservation, National Chung Hsing University, Taichung, Taiwan (changkt@nchu.edu.tw).

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National Chung Hsing University